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Research Article

Understanding Reading Difficulties with The Aid of Eye-Tracking Data and Using Eye-Tracking Data to Improve the Efficiency of NLP Tasks

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ABSTRACT

Introduction: This research investigates the integration of natural language processing (NLP) techniques with eye-tracking data to gain deeper insights into cognitive processes during reading. By analyzing eye movements, such as saccades and fixations, the study aims to enhance NLP models' accuracy and efficiency in processing text complexity and comprehension.

Objectives: This study objective is to analyze eye-tracking data to understand cognitive processes in reading, identify patterns linked to reading difficulties, and enhance NLP models for tasks like semantic analysis and readability evaluation. Additionally, it addresses methodological and technical challenges in integrating eye-tracking data into NLP systems.

Methods: The research utilizes the Tsukuba Eye-tracking Corpus (TECO), which contains data from Japanese students learning English. Two machine learning models—random forest and linear regression—are applied to analyze eye movement patterns. Feature engineering techniques, including data cleaning, feature selection, and outlier handling, are employed to extract syntactic and semantic complexities.

Results: Findings reveal that eye-tracking data provides valuable indicators of text complexity and reader comprehension. The machine learning models effectively correlate eye movement patterns with reading performance, demonstrating the potential of integrating cognitive signals into NLP applications.

Conclusions The study highlights the benefits of using eye-tracking data to enhance NLP tasks, including machine translation, text completion, and summarization. The results suggest that incorporating cognitive signals into NLP systems can lead to more efficient and accurate models, offering advancements in human-computer interaction and artificial intelligence applications.

Keywords: Eye-Tracking, Natural Language Processing (NLP), Cognitive Processes, Machine Learning, Text Complexity

INTRODUCTION

The integration of eye-tracking data with natural language processing (NLP) offers an exciting opportunity to significantly improve our understanding of the reading process and the cognitive mechanisms involved, while increasing the performance and effectiveness of NLP systems (Glandorf & Schroeder, 2021). Despite considerable progress in both eye-tracking and NLP technologies, the combination of these two areas is still relatively unexplored, leaving much room for development. NLP has made remarkable pro-gress in tasks such as machine translation, language generation and information retrieval, enabling machines to interpret and generate human speech (Mucaj et al., 2025).

However, de-spite these successes, NLP still faces challenges when it comes to tasks that require deep cognitive understanding, such as prioritizing, interpreting and processing in-formation when reading (Hollenstein et al., 2021). These challenges are particularly evident when it comes to the complex cognitive task of reading, which involves not only decoding symbols but also extracting meaning from text (Abusamra et al., 2020; Pirovano et al., 2021). This process requires considerable cognitive effort as the brain is constantly working to integrate visual input, memory and atten-tion. Eye movements, particularly those of the fovea — the central part of the retina responsible for sharp vision — are crucial to this process (Gegenfurtner, 2016). They help the reader to focus on small sections of text and move quickly across the page, adjusting their gaze to the need to understand the material at hand. These movements provide valu-able insights into how a person interacts with the text, such as where they focus their attention, how often they re-read certain sections and where they encounter difficul-ties. Although eye-tracking data can provide detailed information about these cogni-tive processes, it has not yet been widely integrated into NLP systems to improve their capabilities (Tabaku et al., 2025).

NLP alone uses techniques such as tokenization, syntactic parsing and semantic analysis to process and understand language, but these methods do not capture the nuanced cognitive aspects of reading (Ahidi Elisante Lukwaro et al., 2024). For example, NLP algorithms can process sentences and understand their structure, but they do not fully account for how the human brain prioritizes certain information or how it navigates through complex linguistic structures when reading (Krasniqi, 2017). Eye-tracking data, on the other hand, shows how readers interact with these structures in real time. For example, if the reader has difficulty understanding a sentence or word, their gaze lingers on it for longer or they skip it altogether (Gatcho et al., 2024).

These patterns can indicate cognitive challenges, such as difficulties with attention, comprehension or memory. By combining eye-tracking data with NLP, researchers and developers can create more sophisticated models that better mimic human reading behavior, improve language comprehension, and en-hance tasks such as semantic interpretation, sentiment analysis, and even machine translation (Kalemi et al., 2018, 2023). In addition, this integration could help overcome specific challenges faced by readers with cognitive or learning disabilities and provide better tools for detecting and diagnosing reading difficulties (Krasniqi & Nallbani, 2022).

This study aims to explore the potential of integrating eye-tracking data with NLP systems to improve their performance and gain a deeper understanding of the cogni-tive processes involved in reading. The research will focus on the analysis of eye-tracking data to uncover the cognitive mechanisms underlying reading behavior, e.g. how attention, memory and prior knowledge influence reading strategies (Tabaku & Duçi, 2025). It will also investigate how this data can be integrated into existing NLP frameworks to improve tasks such as semantic analysis, sentiment analysis and other language comprehen-sion tasks. In addition, the study will investigate the technical and methodological challenges associated with merging eye-tracking data with NLP models and address issues of data matching, model training and real-time processing (Kalaja & Krasniqi, 2022).

One of the main goals of this research is to develop more accurate and robust models that can better replicate the complexity of human reading behavior and provide a more nuanced understanding of how readers process and interpret text (Kapçiu et al., 2024). These advances have the potential to have a significant impact in a number of areas including education, healthcare and cognitive science (Krasniqi & Nallbani, 2021). By creating models that can accurately replicate reading behavior, this research could lead to improved tools for the diagnosis and treatment of reading difficulties, as well as better educational resources for people with dyslexia or other learning difficulties (Kalemi & Martiri, 2011).

In addition, this integration could help refine NLP applications for broader uses, from improving accessibility aids to en-hancing AI-based language systems that interact with humans in more natural and intuitive ways (Kaouni et al., 2023). The promising combination of eye-tracking with NLP systems thus offers valuable potential for the development of more precise, human-centered tech-nologies that emphasize cognitive processes and meet the needs of different users (Šola et al., 2024).

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LITERATURE REVIEW

To better understand the connection between Natural Language Processing (NLP) and eye-tracking data, several important studies by different authors are discussed. These studies provide different perspectives on the use of these technologies and their impact on improving NLP systems and understanding reading difficulties, and are intended to provide a foundation for future research in this area (Mishra & Bhattacharyya, 2018).

Understanding reading difficulties requires an understanding of the cognitive and physical processes that our eyes go through when reading. The reading process be-gins when light is reflected from the page and reaches the retina, particularly the fovea, which plays a crucial role due to its high-resolution, light-sensitive cells. During reading, our eyes move in rapid saccades, with brief fixations on the fovea that allow the brain to process important information (Ceple et al., 2025).

This review explores the crucial role of eye-tracking data in understanding human cognition and its integration into natural language processing (NLP) systems. As noted, visual information processing is highly accurate in the center of the fovea but decreases with distance, which explains the benefits of larger text for people with low vision (Dehaene et al., 2010). The limitations of the fovea require efficient eye movements to interpret information over larger areas, with saccades and fixations enabling focused processing (Skaramagkas et al., 2023). Eye trackers provide insight into gaze patterns by capturing movement, duration and location, although conscious attention and fixation do not always coincide (Higgins et al., 2014; Jacob & Karn, 2003).

Research on inattentional blindness shows how focused tasks can lead to important details being overlooked. Eye-tracking data also provide in-sight into reading difficulties, with metrics such as saccade length and fixation dura-tion indicating the complexity of the text (Bryan et al., 2020; Pappas et al., 2005). Local measures, including gaze and fixation duration, provide nuanced insights, while phonological awareness and orthographic representations are key factors in reading development (Quiñonez-Beltran et al., 2024). Frequent reading improves language skills and cognitive per-formance, as shown by (Bryan et al., 2020)) and (Rachuri, 2024).

In NLP, eye-tracking data aligns linguistic features with cognitive focus and helps in tasks such as syntactic parsing, sentiment analysis and named-entity recognition (Barrett & Hollenstein, 2020). Despite these ad-vances, (Wang et al., 2024) note that the application of gaze features remains lim-ited, and (Khurana et al., 2023) emphasize the potential of integrating implicit gaze data with explicit human feedback to improve NLP systems. By revealing linguistic features such as fixation patterns on important words, eye-tracking data offers a way to develop NLP models with more human-like comprehension and processing capa-bilities (Khurana et al., 2023).

DATASET DESCRIPTION

The Tsukuba Eye-tracking Corpus (TECO) is a data set created by researchers at the College of Tsukuba in Japan. It consists of eye-tracking data from 41 Japanese stu-dents learning the English language. The dataset includes 30 English passages with a length of 300-400 with a total of 410,000, eye-tracking metrics such as fixation, saccade, word skip, fixation duration, regression and other relevant measures were recorded during the test. The English passage read by the 41 Japanese students was from the Eiken exams in grades Pre-2 to Pre-1. Eiken is a test used to assess stu-dents' reading, listening and speaking skills in the English language. The TECO eye-tracking data has a wide range of applications in machine learning, cognitive sci-ence, human psychology, computer interaction, and natural language processing, which made it an ideal dataset for this study. It is free and open source and available to anyone who needs a dataset for their research. In the table below are some of the features of used dataset

Table 1. The Eye-Tracking Measures Present in the Tsukuba Eye-tracking Corpus (TECO)

Name	Description
book	Material set (A or B)
subjectid	Id of the subjects (participants)
textid	Id of the reading passage
eiken	Grade of eiken (pre-2nd [p2], 2nd [2], pre-1st [p1])
trialid	Id of trial (paragraph in most cases)
itemid	Id of the word-token (ia)

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ia	Interesting area (word-token)
skip	A binary index of whether a word was skipped during the first pass
nfix	The total count of fixations on a word
tfd	The cumulative duration (ms) of all fixation on a word
regin	A binary index indicating whether a word was regressed from the later part of the text
ffd	The duration (ms) of the first fixation on a word during the first
gd	The sum of the duration (ms) of fixations on a word during the first pass (also known as first-pass reading time)
refix	A binary index indicating whether a word was fixated on more than once during the first pass
reread	A binary index indicating whether a word was fixated on after the first pass
rpd	The sum of the duration from when a word was first fixated on until the gaze is directed away from the word to the right, including the time spent during regressions from the word (also known as go-past time)

Table 2. The Participants Details

Name	Description
Id	Id of the subjects (participants)
Sex	Sex of the participants
Age	Age of the participants
book	Material set (A / B)
pro	Score of the reading proficiency test
Conf.1	Confidence ratings on the general English language proficiency
Conf.2	Confidence ratings on reading comprehension skill in English
Conf.3	Confidence ratings on reading speed in English
Conf.ave	Average confidence ratings

Table 3. TECO Word Info

Name	Description
Textid	Id of the reading passage
Itemid	Id of the word-token (ia)
ia	Interesting area (word-token)
position	Location of the word in a passage (from 1 to the maximum word count of the passage)
Length	Word length (number of characters)
freq	Word frequency (from levels 1 to 8 based on the New JACET 8000 List of Basic Words)
pun	Words that has punctuation (e.g., comma, period)
lmost	words at the left-most edge of the line appearing on the screen
rmost	word at the right-most edge of the line appearing on the screen

RESEARCH METHODOLOGY

This research aims to investigate the relevant problems of reading. Based on the collected data, we can develop a robust and efficient NLP system that can help us perform human-like activities. By using eye-tracking, we want to investigate the relationship between the reading behavior, the type of text and the performance level of the reader and find out how these characteristics affect the general art of reading (Patil et al., 2023). In doing so, we utilize the power of machine learning models such as random forest and linear regression (Wang et al., 2024). The aim of this research is to investigate how different linguistic structures affect reading and comprehension. From this information we can develop a good NLP model that can support us in our daily activities (Yang et al., 2023). This methodology describes the steps and methods we used to collect, analyze and process our data. The step-by-step approach of my research methodology is ex-plained below.

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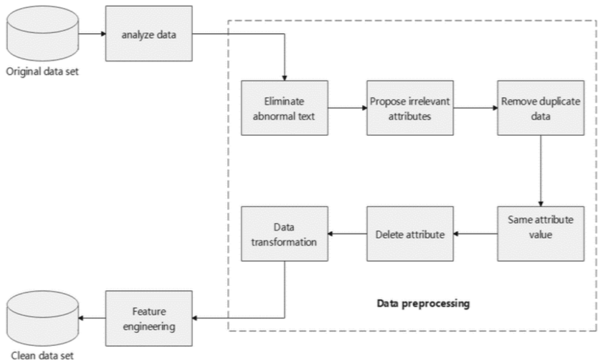

Fig 1. A Flowchart of a Research Methodology Proces

Data Collection

Collecting data is an important aspect of machine learning, as models learn from historical data. The source of the data must be carefully considered, as private data may require the consent of the owner, while public data is freely available. For this project, the publicly available Tsukuba Eye-tracking Corpus (TECO) from OSF.IO is used. This dataset contains eye-tracking data of Japanese L2 English learners read-ing texts and provides valuable insights for the analysis (Tabaku et al., 2025).

Data Preparation

In data processing, the data is prepared in such a way that it enables predictions to be made with good accuracy. However, certain steps are necessary for this to succeed.

Dataset Importation

Based on the type of data and the presence of certain alphanumeric characters, three different data sets are imported. The parameter encoding=latin1 is used to avoid encoding problems, regardless of the characters present. All special characters are then removed from the data set. The dot column's function is used to remove special characters from the column names and the replace function is called to replace these characters with an empty string (Kosova, R., Kapçiu, R., Hajrulla, S., & Kosova, A. M.2023).

```
[ ] #import the 3 datasets

    wordmeasure_df = pd.read_csv('wordmeasure_v1.csv', encoding='latin1')
    participant_info_df = pd.read_csv('participant info_v1.csv', encoding='latin1')
    word_info_df = pd.read_csv('word info_v1.csv', encoding='latin1')

    wordmeasure_df.head()
```

	book	subjectid	textid	eiken	trialid	itemid	ia	skip	nfix	tfd	regin	firstfix.prog	ffd	gd	refix	reread	rpd
0	A	3	1	p2	2	1	Many	1.0	0.0	0.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1	A	3	1	p2	2	2	people	0.0	1.0	104.0	0.0	1.0	104.0	104.0	0.0	0.0	104.0
2	A	3	1	p2	2	3	dream	1.0	0.0	0.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	A	3	1	p2	2	4	of	0.0	2.0	342.0	1.0	1.0	95.0	95.0	0.0	1.0	95.0
4	A	3	1	p2	2	5	becoming	0.0	2.0	504.0	0.0	1.0	263.0	504.0	1.0	0.0	504.0

Fig 2. Data Importation

Table Merge

The data set consists of three separate tables that are merged using a left-join tech-nique with the help of primary keys that exist in these tables. This approach, bor-rowed from SQL, merges tables based on primary keys that also serve as foreign keys in related tables. For example, the participant data contains primary keys such as the topic ID and the book ID, which act as foreign keys in other tables. Once the tables have been merged, the df. head function is used to obtain a preview of the combined data set.

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```
#table that contains participants data + eye data

participantTable = pd.merge(wordmeasure_df, participant_info_df, on=['subjectid', 'book'], how='left')
participantTable.head()
```

	book	subjectid	textid	eiken	trialid	itemid	ia	skip	nfix	tfd	...	refix	reread	rpd	sex	age	pro	conf.1	conf.2	conf.3	conf.ave
0	A	3	1	p2	2	1	Many	1.0	0.0	0.0	...	NaN	NaN	NaN	F	22	15	5	5	5	5.0
1	A	3	1	p2	2	2	people	0.0	1.0	104.0	...	0.0	0.0	104.0	F	22	15	5	5	5	5.0
2	A	3	1	p2	2	3	dream	1.0	0.0	0.0	...	NaN	NaN	NaN	F	22	15	5	5	5	5.0
3	A	3	1	p2	2	4	of	0.0	2.0	342.0	...	0.0	1.0	95.0	F	22	15	5	5	5	5.0
4	A	3	1	p2	2	5	becoming	0.0	2.0	504.0	...	1.0	0.0	504.0	F	22	15	5	5	5	5.0

5 rows × 24 columns

Fig 3. Table merge for participant info and word measure

Data Exploration

Data exploration is one of the first steps you take if you want to extract valuable information from your dataset. In a vast sea of data, researchers use data exploration to get an overview of the content of the dataset, familiarize themselves with the data, understand its organization, and find priceless insights hidden beneath the surface (Elezaj et al., 2018; Nallbani & Krasniqi, 2023). We use this process to look for characteristics such as column data and the type of values it contains, whether they are floating point numbers, strings or integers (Blascheck et al., 2017; Ryabinin et al., 2023).

Data Cleaning

Data cleansing, also known as data scrubbing, is about identifying and removing errors, inconsistencies and inaccuracies to ensure the accuracy, consistency and reli-ability of the data set. In the dataset, df. isna (). sum () was used to identify missing values and visualize them in a heatmap. The heatmap showed that columns such as "region"," "ffd"," "refix" and "rpd" had the most missing values. To fix this, I used imputation methods which can be either median, mode or mean (central tendency methods) to fit the data. Mode imputation was applied to categorical columns (e.g. 1/0, yes/no), while median imputation was used for non-categorical columns to en-sure the data was more centralized and less skewed (Koo et al., 2018; Ndou et al., 2019).

Detection and Removal of Outliers

This is the part responsible for determining the degree of variability of the data set compared to the mean. Outliers are identified by determining the interquartile range and visualizing outliers for each measure or selected columns and applying the cap-ping technique to remove the outliers (Atweh et al., 2024).

Data Standardization

Data standardization is about converting the data into a uniform format and ensuring uniform naming, formatting and classification. For the data set used, the standard scalar function is applied to key columns such as fixation, gaze duration, word length, word frequency and regression (Tabaku, 2024, 2025). After standardization, fixation duration is plotted against word length. This revealed a hump shape indicating that words with more fixations typically had a length between one and three. A correlation analysis was then performed to determine the relationships between the columns. The heatmap showed positive correlations, e.g. between "pro" and "conf1"," "conf2"," "conf3" and "conf.avg"," while "word length" and "skip" showed a negative correla-tion, with blue indicating negative and red positive correlations (Adelman, 2012; Chateau & Jared, 2000).

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Data Normalization and Standardization

```
[ ] """ The selected features are the most popular features without the benefit of doubt have a correlation with eye tracking dataset.
    They were selected to be scaled.... they are mostly of fixation, gaze duration, word length, word frequency, regression. """

    # Select numerical features for standardization
    features_to_scale = ['length', 'freq', 'nfix', 'tfd', 'ffd', 'gd', 'rpd']

    scaler = StandardScaler()

    df[features_to_scale] = scaler.fit_transform(df[features_to_scale])
```

Fig.4. Highlight of Features to be Standardised

Feature Engineering

In the pre-processing phase of the data, new features were created to improve feature extraction and increase the accuracy of predictions. These new columns include:

Total Fixation Time: This feature is calculated by multiplying the number of fixa-tions (Nfix) by the total fixation duration (Tfd) and helps to understand the total duration of fixations.

Regression Ratio: This feature was calculated by dividing the number of repetitions of a word by the total number of fixations. It helps to measure the degree of repeti-tion and understand the sentence or word structure, especially the syntactic complex-ity.

Word Difficulty: This function is calculated by multiplying the word length by the frequency of occurrence and assesses the difficulty of words based on their size and frequency.

Participant Competence: created by multiplying performance by the confidence mean, this function provides an indication of the participant's overall level of com-petence.

Context features: The context of the text was determined by concatenating the left and right sides of the text.

Once these features were established, a correlation matrix was created. The target variable Participant Proficiency showed a positive correlation with features such as pro, conf1, conf2, conf3 and conf.avg, as well as some negative correlations.

[3] Feature Engineering

```
[ ] # Example: Creating total fixation time and regression ratio
    df['total_fixation_time'] = df['nfix'] * df['tfd']

    df['regression_ratio'] = df['reread'] / df['nfix']
```

```
[ ] # We already have word length and frequency in the dataset, since we haven't decided yet on doing syntactic complexity
    #we can still create this feature regardless to boost our feature selection options

    # Recall, syntactic complexity is all about the structure of the sentence hence, we derive that from word positions and differenciate words that have punctuations
     #(e.g., based on position and punctuation)
    df['syntactic_complexity'] = df.apply(lambda x: x['position'] if x['pun'] else 0, axis=1)
```

```
[ ] #Create new feature to know Word Difficulty Score
    df['word_difficulty'] = df['freq'] * df['length']

    #Create new Participant Proficiency Score
    df['participant_proficiency'] = df['pro'] * df['conf.ave']
```

Fig 5. Feature Engineering Procedure

Feature Selection

Feature selection is about deleting all features that are not conducive to my models, i.e. that do not correlate well enough with my model. After feature selection, a dis-tribution analysis is performed and outliers are identified. This is done to understand the distribution of our data points. We try to figure out if they are right or left skewed, and then we also try to remove outliers within our data. I used the histogram to determine the distribution of my data points and the boxplot to visualize my out-liers. Based on the distribution of my data points, most of my features are correctly distributed, with the exception of frequency and length.

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Model training

The idea behind our training is that we want to create our predictors and target vari-ables. Our predictors are X, the features we selected during feature selection, and Y, my target variable, is what we want to predict, namely participant performance. The train test split function of scikit learn was used to split the data into a training part and a test part. Following the 80/20 rule, where 80% of the data set is used for train-ing and 20% for testing and validation, I used the linear regression model and the Radom Forest model.

Model Training

```
x = dt[['age',
  'pro',
  'conf.1',
  'conf.2',
  'conf.3',
  'conf.ave',
  'length',
  'freq',
  'total_fixation_time',
  'syntactic_complexity',
  'word_difficulty']]

y = dt['participant_proficiency']

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)
```

Fig. 6: Model Training Prerequisites

RESULS

This research has achieved important milestones in the analysis of text complexity, semantic meaning and the integration of eye-tracking data to account for individual reading needs.

The study began with importing and merging the required data and libraries, fol-lowed by sifting, cleaning, standardizing and normalizing the data to ensure con-sistency. A correlation analysis revealed a moderate distribution of data points, and outliers were identified. For syntactic analysis, the sentences in the dataset were broken down into individual words, which were stored in separate columns. These were later grouped by text ID to reconstruct complete sentences and paragraphs. This step enabled the assessment of syntactic complexity through measures such as sen-tence length, subordinate clauses and part-of-speech (POS) tagging. Longer sentenc-es were found to have higher syntactic complexity compared to shorter ones, and the identification of subordinate clauses and conjunctions provided insights into sen-tence structure and flow. Semantic analysis focused on understanding the meaning of sentences using techniques such as sentence reconstruction and the LESK algo-rithm, which assigns meaning to words based on their context. The LESK algorithm was particularly effective in clarifying the overall meaning of sentences and showed potential for applications in text completion algorithms. The results were visualized by plotting syntactic complexity against text ID, revealing how sentence structure varied across the dataset. The combined syntactic and semantic analyzes contribute to advances in text processing and accessibility, with applications in natural lan-guage understanding, machine translation and user-centered language systems

CONCLUSIONS

The results of this research underline the importance of syntactic complexity analy-sis for the further development of natural language processing (NLP) tasks. By ena-bling the distinction between simple and complex sentence structures, the analysis provides crucial insights for applications such as machine translation and AI-based summarization of documents. Sophisticated models capable of interpreting complex syntactic structures are essential for an accurate understanding of sentence context within a broader textual framework.

In addition, syntactic complexity proves valuable for contextual categorization of text, allowing AI models to group content effectively. For example, AI can catego-rize humor and comedy separately from horror or tragedy by analyzing sentence structures, conjunctions and phrases. This ability to recognize contextual meanings improves sentiment analysis and facilitates the recommendation of content tailored to specific audiences, such as educational material for students or political content for adults.

Finally, while noise in eye-tracking datasets can be challenging, the data collected in this study had minimal noise, as shown by the distribution analysis. This ensures the reliability of eye-tracking insights used in conjunction with NLP models, further improving their performance and applicability in various tasks.

As for the potential issue of noise in eye-tracking datasets, the noise in our dataset was minimal, as you can see in the data distribution figure below.

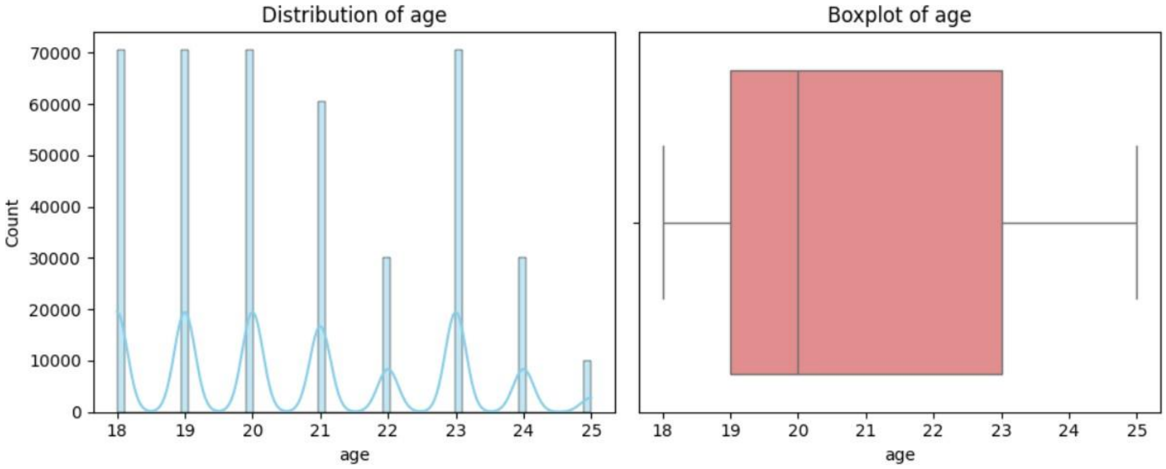

Fig 7. Image showing the presence of less noise in the dataset

Integrating eye-tracking data into tasks such as text complexity assessment and summarization provides a personalized approach to address individual reading needs. Eye movement patterns, which are closely linked to cognitive processes, offer valuable insights into the way readers interact with texts. By using this data to sim-plify complex texts or sentences, we can reduce the cognitive load, making it easier for individuals to engage with and complete reading tasks. This approach not only improves readability, but also overall accessibility and user experience in NLP-driven applications.

RECOMENDATION

Future research should explore languages beyond English to gain deeper insights into the complexity of different languages, which could help improve NLP models for real-world applications. Advanced models such as transformers and deep learn-ing techniques should be applied to eye-tracking data to improve the performance and accuracy of NLP systems. In addition, NLP researchers should invest in under-standing cognitive psychology and neuroscience, as insights into human cognition can guide the development of algorithms that perform at a human-like level and thus increase their effectiveness. Efforts should also be made to reduce noise in eye-tracking data by improving the calibration of hardware and using advanced data pre-processing techniques to clean the dataset. Finally, strict rules and guidelines should be established to ensure the integrity of data collection and analysis, while user pri-vacy policies must be strictly adhered to.

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